REACT: The Riskmap Evaluation and Coordination Terminal

by

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Abstract

The United Nations Office for Disaster Risk Reduction (UNDRR) states that economic losses due to natural disasters have risen 151 percent in the past 20 years. Of these disasters, floods are the most common. The Sendai Framework for Disaster Risk Reduction was created by the UNDRR in order to chart goals for future risk mitigation; among its seven global targets is increasing the availability of disaster risk information and assessment systems. Disaster information systems use state of the art techniques such as remote sensing in order to mitigate damages from natural and man made hazards.

More developed countries utilize networks of advanced sensors and ahead of time mapping in order to facilitate emergency responses; however, such systems are not available in developing countries due to cost limitations. The widespread proliferation of smart phones and social media use in developing countries means that citizens can be used as sensors by reporting disaster information online. The Riskmap system was developed by the Urban Risk Lab at MIT in order to gather citizen report streams. Such citizen disaster reports have two issues: a large influx of reports can cause information overload in emergency operations centers, which makes it difficult to summarize the situation. Machine learning has previously been used in order to analyze and simplify information for human consumption. This work seeks to use novel machine learning techniques to fully utilize crowdsourced social media reports gathered using the Riskmap system.

First we establish the motivation for using citizens as sensors and analyzing this noisy data using machine learning. We then review different machine learning techniques that have been used in crisis information systems, including those that also utilize social media. Finally a novel ensemble learning model is presented that can accurately predict large flood events from crowdsourced data.

Thesis Supervisor: Miho Mazereeuw
Title: Associate Professor

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Chapter 1

Introduction

Flooding is the most common natural disaster in the world [7]. Flood related deaths account for half of all deaths from natural disasters [20]. Although flooding impacts both developed and developing countries, developing nations face much worse consequences as a result of flooding since they lack resources to adequately mitigate disasters [24]. Unregulated urbanization, rising population and climate change are all contributing to increase the rate at which floods occur in developing megacities; furthermore, there is little data about these disasters [15]. Data scarcity makes it hard to pinpoint where to direct aid during disasters and where to make infrastructure improvements after disasters [25].

Various stakeholders have different but overlapping interests with regards to disaster management. Government and NGOs work together to provide relief from mitigate damages from flooding [6]. Citizens look for relevant flood information and try to reduce their risk [34]. Information is at the core of this interaction; however, data scarcity makes it hard for emergency personnel to optimize their use of resources, while citizens have an abundance of information about their surroundings but must be careful not to trust incorrect or outdated information about broader areas [23]. The natural solution is for citizens on social media to submit real time reports to the Emergency Operations Center (EOC), which is tasked with using those reports to inform citizens. There is one problem with this solution, in times of crisis EOCs can suffer from information overload when they are presented with too much information [29].

The REACT system uses novel machine learning and human computer interaction research to reduce information overload in EOCs, thereby decreasing disaster response time. REACT learns how Emergency Operations Centers (EOCs) classify the severity of flood events given citizen submitted reports. REACT trains itself through a gamified simulation of a disaster event. During a real disaster, REACT digests social media reports and estimates how severely an event is impacting different areas of a city and thereby helps EOCs to respond in the best manner possible.

1.1 Emerging Risk In South and Southeast Asia

Global climate change is 'expected to increase the frequency and intensity of floods' [1]. Urban areas are particularly at risk from flooding; unchecked development and rising population have created megacities that regularly experience flooding [7]. Nowhere is this more apparent than in South and Southeast Asia, where the severity of floods has been increasing over the past several decades [30].

Of the world's 33 megacities, over 60 percent are located in developing Asian Countries [32]. These cities face a looming crisis as flood risk increases, but there are also unique opportunities for risk mitigation. Megacities are characterized by high population density. This high density leads to an increase in economic damages and loss of life, but it also means that there are large numbers of citizens that have disaster information they would like to share with others [7].

1.2 History of Disaster Informatics

One of the best known and earliest

Work in Mapping disasters epidemiology John Snow's use of maps to find the source of Cholera outbreak in London[26].

In more recent times, the need for Information Technology (IT) in disaster management has been clear since the mid 1980s when computers became user friendly enough to be used during disasters [33]. Now many EOCs use Geographic Information Systems (GIS) in order to organize spatial data and analyze disaster information; however, researchers have often stated that 'there are many reasons to remain skeptical about the idea that technology will provide a panacea for emergency management problems' [31, 29, 22]. A number of potential negative effects associated with IT disaster management technology have been identified: the potential for the technology to increase social inequality, the potential of information overload, and the dissemination of incorrect and outdated information [23, 10].

For flooding: [1]

Technology can help disaster response; however, it also has the ability to cause information overload[29]

1.2.1 Social Media and disasters

The history of social media and the hashtag is invariably linked to disaster communication. It was during the San Diego bush fires of 2007 that the hashtag was first widely used on twitter [27].

Much work has been done in passively listening to social media streams in order to better understand how disasters unfold and how humans use social media as a communication tool during disaster events. Many of these studies use hand labeled tweets in order to analyze which percentage of them

Digital Humanitarians use twitter to help spatially locate needs in Haiti after the 2008 earthquake [15]

Twitter tale of 3 hurricanes [3]

1.3 The Riskmap System

1.3.1 Motivation for crowdsourced data

Citizens as sensors Geosocial intelligence Holderness [11].

Quarantelli emphaszied that 'management of hazards is fundamentally social in nature and not something that can be achieved strictly through technological upgrading' [29] yet social media brings human behavior into a machine readable format that can be used to provide further information during disasters.

1.4 Motivation for Machine Learning

Chapter 2

Previous Work

2.1 Machine Learning in Crisis Informatics

2.1.1 Passive Listening

Using social media in order to obtain on the ground information about disasters, both anthropogenic and otherwise, is as old social media itself. One of the first

The usefulness of social media

Most of the work in this area has been done by passively listening to twitter posts or facebook comments.

Some was looking for clues after disasters: [34] problem: don't have real time results

Some used humans to filter out social media for real time disaster info [28] [15]

Some involved using machine learning: [12]

Problems with that approach:

It is very difficult to filter out which social media images are related to the disaster and which are not.

2.1.2 On Image Data

Online learning using traditional transfer learning [9] but online (so they get people to label images as a disaster happens?) plus train with generic disaster images in order to solve cold start problem at the beginning of an event. Classify social media images into 3 classes: (severe, mild, little) damage. [18]

2.1.3 On Text Data

Crowd sentiment detection during disasters using twitter and the 2010 San Bruno CA fires n=3698 [17]

Feature engineering on twitter messages to classify into pre-incident, during incident and post-incident [8]

Classifying tweets as informative/ not informative using CNNs vs SVMs (CNN wins) [5]

CrisisNLP from the Qatar Computing Research Institute has a huge datasets [19]

2.1.4 Ensemble Data Models

This paper [16] uses deep learning to identify damage related info

Low level visual features (extract color, shape texture) + then Use bag of words on the text. Make a [14]

2.1.5 Common Difficulties

Task Subjectivity

Task subjectivity is an incredibly common issue [18, 24]. While most humans can agree on whether an object is or is not an apple, this task does not translate to defining if a picture indicates a severe event or a minor one.

In other words, people's perception of risk varies widely from region to region and from citizen to citizen [24].

Small Datasets

Although larger datasets have recently become available, there has historically been a scarcity of training and validation data available for crisis detection [13, 2]. Deep learning models that are trained on small datasets tend to overfit on the training data and do not generalize well to the validation dataset [21].

In many early studies only hundreds of data points were considered— combined with the small size of those data points (for example, twitter microblogs of 140 or 280 characters) and effectively using deep learning becomes very difficult. For example [17] only uses 3,698 tweets in order to train

Connects citizens to EOC

As discussed in 1.3, the Riskmap system helps to connect citizens to Emergency Operations Centers

Focus on technology rather than whole system design

A series of UN case studies on six disaster information systems found that while engineering and system design were essential, it was the hidden wiring of

> An important message emerges from the case studies: an effective disaster information management system requires a good technological platform, but also much more. Software programs for storing, sharing, and manipulating data for disasters are being developed or patched together at a steady pace, often in the aftermath of disasters. The real difficulty lies in anchoring these technological approaches in an appropriate institutional context where they are supported by relevant and effective operating procedures, agreed terminology and data labeling, and a shared awareness of the benefits of proper handling of disaster information. Clearly, a disaster information management system must be supported by accepted rules, procedures, and relationships that encourage, facilitate, and guide the production, sharing, and analysis and use of data in response to disaster.

In these case studies, the institutional dimension—the hidden wiring—determined the effectiveness of the systems. [4]

Chapter 3

Methodology

3.1 Data Description

The Riskmap system allows citizens to easily submit disaster reports 1.3; as such it has allowed the Urban Risk Lab at MIT to gather thousands of reports of real flooding in Indonesia and India.

3.1.1 Image Data

3.1.2 Text Data

3.1.3 Flood Height

3.1.4 Location Information

Chapter 4

Results

4.1 Individual

4.1.1 Image Data

4.1.2 Text Data

4.1.3 Flood Height

4.1.4 Location Information

4.2 Bagging

Appendix A

Tables

Table A.1: Armadillos

Armadillos	are
our	friends

Appendix B

Figures

Figure B-1: Armadillo slaying lawyer.

Figure B-2: Armadillo eradicating national debt.

Bibliography

[1] Mike Ahern, R. Sari Kovats, Paul Wilkinson, Roger Few, and Franziska Matthies. Global Health Impacts of Floods: Epidemiologic Evidence. *Epidemiologic Reviews*, 27(1):36–46, July 2005.

[2] Firoj Alam, Ferda Ofli, and Muhammad Imran. CrisisMMD: Multimodal Twitter Datasets from Natural Disasters. page 9.

[3] Firoj Alam, Ferda Ofli, Muhammad Imran, and Michael Aupetit. A Twitter Tale of Three Hurricanes: Harvey, Irma, and Maria. *arXiv:1805.05144 [cs]*, May 2018.

[4] Samia Amin and Markus P. Goldstein, editors. *Data against Natural Disasters: Establishing Effective Systems for Relief, Recovery, and Reconstruction.* World Bank, Washington DC, 2008. OCLC: ocn185123397.

[5] Cornelia Caragea, Adrian Silvescu, and Andrea H. Tapia. Identifying informative messages in disaster events using Convolutional Neural Networks. In *ICIS 2016*, 2016.

[6] F. K. S. Chan, C. Joon Chuah, A. D. Ziegler, M. Dąbrowski, and O. Varis. Towards resilient flood risk management for Asian coastal cities: Lessons learned from Hong Kong and Singapore. *Journal of Cleaner Production*, 187:576–589, June 2018.

[7] Faith Ka Shun Chan, Gordon Mitchell, Olalekan Adekola, and Adrian McDonald. Flood Risk in Asia's Urban Mega-deltas: Drivers, Impacts and Response. *Environment and Urbanization ASIA*, 3(1):41–61, March 2012.

[8] Soudip Roy Chowdhury, Muhammad Abdullah Imran, Muhammad Rizwan Asghar, Sihem Amer-Yahia, and Carmen Castillo. Tweet4act: Using incident-specific profiles for classifying crisis-related messages. In *ISCRAM*, 2013.

[9] Jeff Donahue, Yangqing Jia, Oriol Vinyals, Judy Hoffman, Ning Zhang, Eric Tzeng, and Trevor Darrell. DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition. *arXiv:1310.1531 [cs]*, October 2013.

[10] Felix Flentge, Stefan G Weber, Alexander Behring, and Thomas Ziegert. Designing Context-Aware HCI for Collaborative Emergency Management. *1987*, page 4.

[11] Tomas Holderness and Etienne Turpin. From Social Media to GeoSocial Intelligence: Crowdsourcing Civic Co-management for Flood Response in Jakarta, Indonesia. In Surya Nepal, Cécile Paris, and Dimitrios Georgakopoulos, editors, *Social Media for Government Services*, pages 115–133. Springer International Publishing, Cham, 2015.

[12] Muhammad Imran, Shady Elbassuoni, Carlos Castillo, Fernando Diaz, and Patrick Meier. Practical extraction of disaster-relevant information from social media. In *Proceedings of the 22nd International Conference on World Wide Web - WWW '13 Companion*, pages 1021–1024, Rio de Janeiro, Brazil, 2013. ACM Press.

[13] Muhammad Imran, Prasenjit Mitra, and Carlos Castillo. Twitter as a Lifeline: Human-annotated Twitter Corpora for NLP of Crisis-related Messages. page 6.

[14] H. S. Jomaa, Y. Rizk, and M. Awad. Semantic and Visual Cues for Humanitarian Computing of Natural Disaster Damage Images. In *2016 12th International Conference on Signal-Image Technology Internet-Based Systems (SITIS)*, pages 404–411, November 2016.

[15] Patrick Meier. *Digital Humanitarians: How Big Data Is Changing the Face of Humanitarian Response*. CRC Press, Inc., Boca Raton, FL, USA, 2015.

[16] Hussein Mouzannar, Yara Rizk, and Mariette Awad. Damage Identification in Social Media Posts using Multimodal Deep Learning. page 16, 2018.

[17] Ahmed Nagy and Jeannie A. Stamberger. Crowd sentiment detection during disasters and crises. In *ISCRAM*, 2012.

[18] Dat T. Nguyen, Ferda Ofli, Muhammad Imran, and Prasenjit Mitra. Damage Assessment from Social Media Imagery Data During Disasters. In *Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017*, ASONAM '17, pages 569–576, New York, NY, USA, 2017. ACM.

[19] Dat Tien Nguyen, Kamela Ali Al Mannai, Shafiq Joty, Hassan Sajjad, Muhammad Imran, and Prasenjit Mitra. Rapid Classification of Crisis-Related Data on Social Networks using Convolutional Neural Networks. page 10.

[20] C. A Ohl. Flooding and human health. *BMJ*, 321(7270):1167–1168, November 2000.

[21] Luis Perez and Jason Wang. The Effectiveness of Data Augmentation in Image Classification using Deep Learning. *arXiv:1712.04621 [cs]*, December 2017.

[22] Marcia Perry. Natural disaster management planning: A study of logistics managers responding to the tsunami. *International Journal of Physical Distribution & Logistics Management*, 37(5):409–433, June 2007.

[23] E. L. Quarantelli. Problematical aspects of the information/ communication revolution for disaster planning and research: Ten non-technical issues and questions. *Disaster Prevention and Management; Bradford*, 6(2):94–106, 1997.

[24] E. L. Quarantelli. Urban Vulnerability to Disasters in Developing Countries: Managing Risks. In Alcira Kreimer, Margaret Arnold, and Anne Carlin, editors, *Building Safer Cities: The Future of Disaster Risk*, pages 211–231. Disaster Risk Management Series., 2003.

[25] Irfan Ahmad Rana and Jayant K. Routray. Multidimensional Model for Vulnerability Assessment of Urban Flooding: An Empirical Study in Pakistan. *International Journal of Disaster Risk Science; Heidelberg*, 9(3):359–375, September 2018.

[26] Simon Rogers. John Snow's data journalism: The cholera map that changed the world. *The Guardian*, March 2013.

[27] Eduardo Salazar. Hashtags 2.0 - An Annotated History of the Hashtag and a Window to its Future. *Revista ICONO14 Revista científica de Comunicación y Tecnologías emergentes*, 15(2):16–54, July 2017.

[28] Kate Starbird and Leysia Palen. Voluntweeters:" Self-organizing by digital volunteers in times of crisis. In *Proc. of CHI (2011*, pages 1071–1080.

[29] Kathleen J. Tierney, Michael K. Lindell, and Ronald W. Perry. *Facing the Unexpected: Disaster Preparedness and Response in the United States*. Joseph Henry Press, November 2001.

[30] Jacqueline Torti. Floods in Southeast Asia: A health priority. *Journal of Global Health*, 2(2), December 2012.

[31] S. Tzemos and R. A. Burnett. Use of GIS in the Federal Emergency Management Information System (FEMIS). Technical Report PNL-SA-26086; CONF-9505242-1, Pacific Northwest Lab., Richland, WA (United States), May 1995.

[32] United Nations Department of Economic and Social Affairs. *The World's Cities in 2016*. Statistical Papers - United Nations (Ser. A), Population and Vital Statistics Report. UN, September 2016.

[33] of Colorado Boulder University and of Colorado Boulder University. *Terminal Disasters: Computer Applications in Emergency Management*. Number monograph #39 in Program on Environment and Behavior. Institute of Behavioral Science, University of Colorado, Boulder?, 1986.

[34] Sarah Vieweg, Amanda L Hughes, Kate Starbird, and Leysia Palen. Microblogging during two natural hazards events: What twitter may contribute to situational awareness. page 10, 2010.